PRELIMINARY
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The Impact of Public Health Insurance on Labor Market Transitions

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Abstract

An often-cited difficulty with moving low-income families out of welfare and into the labor force is the lack of health insurance in many low-wage jobs. Consequently, many low-income household heads may be reluctant to leave welfare and thereby lose health insurance coverage for their children. The expansions in the Medicaid program to cover low-income children and pregnant women who are not eligible for cash benefits may help alleviate the problem by allowing disadvantaged household heads to accept jobs which do not provide health insurance. We use a discrete time (monthly) hazard rate model and data from several panels of the Survey of Income and Program Participation to assess whether expansion of public health insurance to cover children of working parents contributes to increase transitions out of welfare and into employment and reduce transitions into welfare and out of employment. We model spells in progress and spells that start during the sample separately, which allows us to assess the effect on long-term welfare recipients. We find some evidence that expanded Medicaid eligibility for children leads single mothers to exit welfare more quickly; however the effects are not robust to the inclusion of year effects. In addition, the effect appears to be strongest and most consistent among long-term recipients (as proxied by recipients who begin the sample on welfare). We find less evidence of an effect of expanded Medicaid eligibility on transitions into welfare. A somewhat surprising finding is that higher AFDC income limits also appear to have little effect on the probability of such transitions.

I. Introduction

In the last decade there have been two major policy initiatives aimed at low-income individuals. The Personal Responsibility and Work Opportunities Reconciliation Act of 1996, which "reformed" welfare programs, contained many provisions intended to move women from receiving welfare to becoming employed. The other policy initiative, which began in the mid-1980s and continues today, was an expansion of the public health insurance program Medicaid to cover low-income pregnant women and children who were ineligible for cash assistance. These two policy initiatives, while enacted independently, may in fact prove complementary. An often-cited difficulty with moving low-income families out of welfare and into the labor force is the lack of health insurance in many low-wage jobs. Only about 43 percent of workers with hourly wages of $7 or less are offered health insurance by their employer, in contrast with a greater than 80 percent offer rate among higher-paid workers (Cooper and Schone, 1997). Consequently, many low-income household heads may be reluctant to leave welfare and thereby lose health insurance coverage for their children. The expansions in the Medicaid program to cover low-income children and pregnant women who are not eligible for cash benefits may help alleviate the problem by allowing disadvantaged household heads to accept jobs which do not provide health insurance. In this paper, we assess how expansions of public health insurance to cover children of working parents affect welfare participation and labor supply, focusing on whether such expansions contribute to ease transitions out of welfare to work and whether these expansions reduce transitions from employment or time spent off welfare.

Previous research in this area using cross-sectional data (e.g. Yelowitz, 1995) found evidence that Medicaid eligibility is associated with a higher probability of employment and a lower probability of welfare participation. However expansions in public health insurance can affect the probability that a woman is currently on welfare either by increasing the exit rate from welfare or by reducing the entry rate into welfare. Similarly, Medicaid expansions can affect the probability that a women is employed at a point in time by affecting the average duration of an employment spell and the average duration of a non-employment spell. In this paper we use a discrete time (monthly) hazard rate model and data from several panels of the Survey of Income and Program Participation (SIPP) to examine these effects in a dynamic framework. Specifically, we examine the effect of Aid to Families with Dependent Children (AFDC) benefits and Medicaid expansions on: i) the transition rates into and out of welfare; ii) the transition rates into and out of employment; iii) the specific transition rate from welfare to employment and iv) the specific transition rate from employment to welfare. This approach is particularly appropriate to the problem since it allows us to examine the sources of decreases in welfare participation probabilities, leading to a greater understanding of the mechanism by which Medicaid expansions can affect participation in welfare and employment. This distinction can aid policy, since for example programs that increase employment duration have additional benefits, such as increased human capital accumulation.

Our framework also allows us to examine whether expanded eligibility for children affects long-term welfare recipients differently from individuals who have been on welfare for only a short time. Previous work on welfare (see e.g., Blank 1989) has shown that some welfare recipients have a low probability of leaving welfare (and hence longer spells) while others are likely to leave welfare more quickly. We examine these two groups (long-term and short-term recipients) by considering spells on welfare that are in progress at the beginning of the sampling period (and which are thus likely to contain more long-term welfare recipients) separately from spells which begin during the sampling period. Determining how each group responds to the expansions is likely to be of considerable interest to policy makers given the interest in moving long-term recipients off welfare on a permanent basis.

We have not yet been able to address all of the above issues, and our results should be considered preliminary. We find some evidence that expanded Medicaid eligibility for children leads single mothers to exit welfare or non-employment more quickly; however the effects are not robust to the inclusion of year effects. In addition, the effect appears to be strongest and most consistent among long-term recipients (as proxied by recipients who begin the sample on welfare). We find less evidence of an effect of expanded Medicaid eligibility on transitions into welfare or non-employment. A somewhat surprising finding is that while higher AFDC income limits (or benefits) have a strong effect in terms of reducing the exit rate from welfare or non-employment, they appear to have little or no effect on rate at which individuals enter welfare or non-employment.

The remainder of this paper is organized as follows. In the next section, we summarize the legislative background of the Medicaid expansions and discuss previous research relevant to this paper. In Section III we describe the economic models and the implied econometric approaches that we consider. Section IV is a description of the data, including a discussion of how we capture the effects of the expansions. In Section V we present our preliminary empirical results for some of the models discussed in Section III. We conclude the paper and discuss future work in Section VI.

II. Background

Medicaid is a joint state-federal program providing health insurance to three groups of Americans: low-income aged and disabled people; the "medically needy"–people who qualify for coverage because of large medical expenses; and low-income families with children. Historically, Medicaid eligibility among the third and largest group was tied to eligibility for AFDC. Because AFDC eligibility depended partly on family structure, and because the program's income limit in most states was well below the federal poverty line, the tie to AFDC meant that through the late 1980s, Medicaid covered less than half the families with incomes below the poverty line. It also meant that if a woman were to leave welfare, she and her children would lose their Medicaid coverage. Starting in the mid-1980s, a series of federal laws uncoupled Medicaid eligibility from AFDC eligibility, expanding the population eligible for Medicaid to include poor pregnant women and children previously ineligible for AFDC.[1] Following the federal expansions, many states expanded their Medicaid programs further to include children not covered by the federal mandates.

These laws removed family structure restrictions (allowing children in two-parent families to qualify) and increased the Medicaid income threshold well above the AFDC threshold (to between 100% and 185% of the poverty line and sometimes higher, depending on the year, state of residence, and age of the child), which increased both Medicaid eligibility and coverage substantially. The population of women ages 15 to 45 who would be eligible for Medicaid if they became pregnant doubled between 1987 and 1992 (Cutler and Gruber, 1996), while among

[1]These laws included the Omnibus Budget Reconciliation Acts (OBRAs) of 1986 and 1987, the Medicare Catastrophic Coverage Act and Family Support Act of 1988, OBRA 1989 and OBRA 1990. For a more detailed discussion of the provisions of these laws and their effective dates, see Shore-Sheppard (1997).

children under 15 between 1987 and 1995 the population eligible increased from 17 percent to 31 percent and participation in the program increased from 16 percent to 25 percent (Shore-Sheppard, 1997).

The perceived importance of the Medicaid program in funding health care for children is clear: Medicaid was explicitly exempted from the welfare reform provisions enacted in the Personal Responsibility and Work Opportunities Act of 1996, which eliminated AFDC and replaced it with the Temporary Assistance for Needy Families (TANF) program. Categorical Medicaid eligibility continues to be determined as it had been in the past. In addition, in response to pressure from states and the continuing decline in private insurance coverage for children, in the summer of 1997 Congress and the President enacted a law creating the State Children's Health Insurance Program (SCHIP) which provides states with $40 billion over the next ten years in block grant funding (the largest increase in public spending on insurance for children in three decades) to expand further publicly-provided health insurance for children.

While static models of the effect of Medicaid eligibility on welfare and labor force participation have been estimated using cross-sectional data, the results from these studies have yielded mixed evidence on the effect of health insurance on welfare. In addition, all studies of the impact of Medicaid on labor supply and welfare participation done thus far have used a static (cross-sectional) framework. One difficulty that researchers have faced is how to identify separately the impact of Medicaid on labor supply from the impact of other programs such as AFDC and Food Stamps. Both Blank (1989) and Winkler (1991) calculate a state-specific value of Medicaid and include it in AFDC participation, labor force participation, and hours worked equations. They find generally small and usually statistically insignificant effects of the value of

Medicaid. Moffitt and Wolfe (1992) develop a family-specific proxy for the value of Medicaid and include it in cross-sectional probit equations of AFDC participation and employment. They find effects of Medicaid that are larger in magnitude than found previously, statistically significant, and of the sign predicted by theory, with more valuable Medicaid benefits leading to higher rates of AFDC participation and lower rates of labor force participation. However when they allow the effect of Medicaid to differ for families with low and high values of Medicaid, their estimates indicate that only families with high expected medical expenditures alter their AFDC participation or employment decisions in response to Medicaid availability.

Yelowitz (1995) uses the first few years of Medicaid expansions to examine the effect of Medicaid, comparing AFDC and labor force participation among mothers with a child eligible for Medicaid under the expansion to mothers without a child eligible for Medicaid. Using a static probit model and data from the CPS, he concludes that women with higher levels of Medicaid eligibility for their children independent of AFDC eligibility are more likely to work and less likely to participate in AFDC. Unfortunately, the way the expansions are parameterized in this study does not allow the effects of increases in Medicaid eligibility to be identified separately from any decreases in AFDC eligibility that may be occurring. Consequently, his results do not provide clear evidence that Medicaid eligibility affects employment and AFDC participation.[2]

Our research project integrates work on Medicaid with the literature on the use of longitudinal data to study welfare participation decisions and patterns. An early paper by

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[2]In addition to movements in and out of the labor force, public health insurance may have an effect on job-changing behavior as suggested by the literature on health insurance and job mobility, or "job-lock" (see e.g. Madrian (1994), Holtz-Eakin (1994), or Buchmueller and Valetta (1996).) We do not examine these potential effects in this study, but intend to consider them in future work.

O'Neill, Bassi, and Wolf (1987) examines how the characteristics of welfare recipients influence the time they spend on welfare. They use annual data from the National Longitudinal Survey of Young Women to estimate a discrete duration model of the probability of leaving welfare and find that spell duration is related to various characteristics of potential recipients, including number of children, education, and health status. They conclude that recipients with long spells differ in predictable ways from those experiencing short spells. Blank (1989) also studies the determinants of the length of a spell on welfare, using monthly data from the Seattle/Denver Income Maintenance Experiments and a more complex duration model which incorporates unobserved heterogeneity and a competing risk framework. She finds little evidence that the probability of ending a spell is strongly affected by how long the spell has lasted (duration dependence). Instead she concludes that there appears to be two groups in the population of recipients—one group with a low probability of leaving welfare (and hence longer spells) and another group which is likely to leave welfare more quickly.

More recently, several papers have used the SIPP to examine welfare durations. Fitzgerald (1991) uses the 1984 panel to examine welfare durations, focusing on the effects of measures of spouse availability in addition to previously examined determinants. His basic results are consistent with Blank's (1989) results, and in addition he finds some evidence that spouse availability affects welfare durations for white women, although not for black women. Blank and Ruggles (1996) use the 1986 and 1987 panels of the SIPP to describe dynamic patterns in the relationship between eligibility and participation in AFDC and Food Stamps. They show that many spells of eligibility do not lead to a spell of participation, and that spells which end in participation tend to be concentrated among women for whom the expected benefit is higher.

They estimate a competing risk model where spells of eligibility or participation may end either with a family composition change or an income or other change, and find significant differences in the determinants of the two types of transition rates.

Our study investigates the effect of Medicaid eligibility on all transitions out of welfare, as well as transitions due to a spell ending in employment. Moreover, our study examines the effect of Medicaid eligibility on transitions from employment to non-employment, as well as transitions from employment (off welfare) to welfare. Thus we consider the effects of Medicaid expansions on transitions into and out of welfare and non-employment. We analyze spells in progress at the start of the sampling frame as well as fresh spells that begin after the start of the sample period. Previous studies have focused on fresh spells to avoid the econometric problems that arise with interrupted spells (Heckman and Singer 1984). However, this approach has the disadvantage that most long-term welfare recipients will be in the midst of a spell on welfare when the sample begins and are unlikely to have a fresh spell within the sampling period. We follow Heckman and Singer (1984) and use a separate hazard function (and unobserved heterogeneity term) for spells in progress at the beginning of the sample as a means of investigating the experience of long-term welfare recipients.

III. Economic Models and Econometric Approaches

In this section we consider three different economic models concerning the effect of Medicaid expansions on employment status. For each economic model, we then develop the corresponding econometric model. In each case we consider the simplest possible theoretical model that can generate the corresponding econometric model.

III.1 A Simple Labor Force Participation Model

We first consider a standard static participation model with fixed costs (see, e.g. Cogan 1980), since this theoretical model leads to the econometric specification used on cross-section data by many of the existing studies of the effect of Medicaid expansions on employment status or welfare participation. Thus we analyze the empirical implications of this model when panel data are available. To begin, we assume that a woman can find employment whenever she wants with zero search costs.[3] Individuals face a static budget constraint in each period (there is no borrowing or saving),[4] and utility is additively separable over time. Thus individuals maximize utility period by period. Current period utility is given by $U(y_{it}, l_{it}; \theta_{it})$, where y_{it} denotes income, l_{it} denotes leisure, and θ_{it} denotes unobserved taste variation across individuals. For simplicity, we assume that anyone not employed receives welfare benefits B_{it}, as well as Medicaid insurance, which we assume has a cash value M_{it}. Such an individual also consumes T units of leisure, and thus her utility is $U(B_{it}+M_{it}, T; \theta_{it})$. For someone who works, we assume for simplicity that hours of work are fixed at h_{it} and that she receives w_{it} dollars per hour of work (there is no wage offer distribution for a given individual, although wages differ across individuals.) In the absence of welfare payments, each individual has no unearned income and thus utility while working is given by $U(w_{it} h_{it}, T-h_{it}; \theta_{it})$.

The probability that a woman works is given by $\Pr(I=U(w_{it} h_{it}, T-h_{it}; \theta_{it}) - U(B_{it}+M_{it}, T; \theta_{it}) > 0)$. Now suppose Medicaid is expanded such that she becomes eligible for Medicaid insurance for some of her children (and possibly herself through a state waiver program) which

[3] Thus there is no distinction between out of the labor force and unemployment in this model.

[4] One can drop the assumption of no borrowing or saving while maintaining the same structure of the problem by imposing two-stage budgeting. See, e.g., Blundell, Ham and Meghir (1999).

has a cash value M_1. Her utility while working is now $U(w_{it} h_{it} + M_1, T-h_{it}; \theta_{it})$. and thus the probability that she works is now given by $Pr(I^* = U(w_{it} h_{it} + M_1, T-h_{it}; \theta_{it}) - U(B_{it} + M_{it}, T; \theta_{it}) > 0)$.[5] To implement this model empirically, we follow the literature (e.g. Mroz 1987) and approximate the index function in a given period t as

$$
\begin{aligned}
I_{it}^* &= Z_{it}\gamma + u_{it} \\
&= Z_{it}\gamma + v_i + \varepsilon_{it} .
\end{aligned} \tag{1}
$$

The vector Z_{it} contains variables describing the characteristics of the family and the mother X_{it}, variables that proxy AFDC generosity $AFDC_{nst}$ for a family of size n in state s, and unemployment rates UR_{st}. Then we assume that an individual is employed in period t if $I^*_{it} > 0$. (In the literature researchers analyze i) whether an individual is not employed in a given period and ii) whether an individual is on welfare in a given period somewhat interchangeably. We focus on employment determination here to save space, but discuss below jointly estimating welfare status and employment status.) Note that we have broken the overall error term u_{it} into an individual-specific error term, $v_{i,}$ and a individual-period-specific error term, ε_{it}. If we treat v_i as independent of the explanatory variables in (1), then we will have something analogous to a random effects limited dependent variable model, although we may also want to allow the ε_{it} to be correlated over time for a given individual. In either case, if we assume that u_{it} has a multivariate normal distribution, we would have a multivariate probit model.

[5] It is straightforward to relax many of our assumptions without changing the basic results. For example, to allow for variable hours of work, one simply evaluates utility while working at the optimal hours h_{it}*.

III.2. A Simple Stationary Dynamic Participation Model

One possible criticism of the theoretical labor supply model described above is that it assumes that a woman can find a job instantaneously and at zero cost. In terms of our empirical work, this assumption implies that whether an individual is employed in the previous period does not affect the probability of her being employed this period. For many individuals this is too strong an restriction, since we would expect someone who had a job last month to be more likely to be employed this month.[6] We attempt to allow for this possibility in the following simple economic model by assuming that finding a job usually involves incurring search costs as well as randomness in job offers, so that even if a woman looks for a job, she may not find a job that period. The model is based on Burdett and Mortensen (1977) and Blundell, Ham and Meghir (1999), and will generate a richer econometric model that allows the probability of being employed (and the effect of the independent variables such as the Medicaid provisions on the probability of being employed) to depend on previous employment status.

Specifically, we modify the above fixed cost participation model in the following fashion. A woman can only find a job by searching, and if she searches from unemployment, she incurs monetary search costs s. Conditional on searching, she has a probability α of obtaining a job offer. Individuals who are employed lose their job with probability β. We continue to assume that individuals satisfy a static budget constraint in each period and that each individual faces a single wage (as opposed to a wage offer distribution). Further, we assume that the model is stationary in the sense that all variables are constant over time. There are three possible labor

[6] Of course, this model raises difficult issues of whether those employed last period have a higher employment rate this period because of taste differences or because of true state dependence in the employment probabilities. We will attempt to distinguish between these possibilities in the econometric approach discussed below.

market states: i) non-participation in the labor force, ii) searching for a job, and iii) working. Since search today affects employment prospects next period, we can no longer analyze the individual's participation decision separately period by period. For someone who does not participate in the labor force, current period utility is again given by

(4a) $$U_{ot} = U(B_{it} + M_{it}, T).$$

An individual who searches this period has current utility given by

(4b) $$U_{st} = U(B_{it} + M_{it} - s, T).$$ [7]

Finally, an individual who is currently working has current period utility given by

(4c) $$U_{et} = U(w_{it}h_{it}, T - h_{it})$$

The value function for an individual who does not participate is given by

(5a) $$V_{ot} = U_{ot} + (1 + \rho)^{-1} V_{ot+1},$$

where ρ is the discount rate.

Similarly, the value function for someone searching is given by

(5b) $$V_{st} = U_{st} + (1 + \rho)^{-1} [\alpha V_{et+1} + (1 - \alpha) V_{st+1}],$$

and the value function for an employed individual is given by

(5c) $$V_{et} = U_{et} + (1 + \rho)^{-1} [(1 - \beta) V_{et+1} + \beta V_{st+1}].$$

[7] Note that this formulation of utility assumes that there are no time costs of searching. Relaxing this assumption would not change the results.

Since the model is stationary, the value function is the same each period. Using this fact, reduced form versions of the value functions can be derived in terms of the parameters and the utility functions (see, e.g. Blundell, Ham and Meghir 1999):

(5a′) $$V_o = \rho^{-1} U_o .$$

(5b′) $$V_s = \rho^{-1}\left(\frac{\rho + \beta}{\rho + \alpha + \beta} U_s + \frac{\alpha}{\rho + \alpha + \beta} U_e \right),$$

(5c′) $$V_e = \rho^{-1}\left(\frac{\beta}{\rho + \alpha + \beta} U_s + \frac{\rho + \alpha}{\rho + \alpha + \beta} U_e \right).$$

The probability that a woman searches is just $Pr(V_s > V_o)$, which depends positively on utility while working, and the probability that a woman moves from non-employment to employment is $Pr(V_e > V_o) \cdot \alpha$. The probability of an individual leaving employment is simply the layoff rate β, since given our stationarity assumptions, an individual will never voluntarily leave employment for non-employment unless something in the model changes.[8]

Now consider the Medicaid expansions. These expansions raise the current period utility for employment, and thus raise the value function for both employment and search, but not the value of non-participation. As a result, the expansions increase the probability that an individual searches, and thus the probability that she leaves non-employment for employment. On the other hand, the layoff rate β is constant by assumption. Since increasing current period utility while employed will never induce anyone to leave employment for out-of-the-labor-force, the

[8]We are assuming that to find her first job an individual had to search from unemployment, and thus will prefer employment to non-employment.

expansions have no effect on the transition rate between employment and non-employment in this model.

For comparison, consider the case where the Medicaid provisions are constant but AFDC benefits increase. For some individuals, this increase in benefits will raise current period utility while not searching, U_o, above current period utility while working, U_e. In this case, the individual will quit work. Thus we would expect an increase in AFDC benefits to increase the transition rate from employment to non-employment. An increase in benefits will also affect the probability that an individual who is out of work searches. We would expect an increase in benefits to reduce the transition rate from non-employment to employment, although there is the possibility that the effect is ambiguous.[9] This discussion suggests that the probability an individual is employed in a given period depends in an important way on whether she was employed in the previous period. The simplest way to capture this is to generalize the probit equation (1) by allowing lagged employment status to enter the index function

$$I_{it}^{*} = Z_{it}\gamma + \delta I_{it-1} + v_i + \varepsilon_{it}, \tag{6}$$

where I_{it-1} equals one if the individual was employed last period and zero otherwise. This extension is a simple way to account for possible serial persistence in employment or welfare participation, which none of the existing studies of Medicaid's effects are able to do (as they all use cross-sectional data). This model has been previously estimated in similar contexts by Chay and Hyslop (1998) and by Keane and Wolpin (1998).

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[9] To see this, subtract equation (5a') from (5b') and differentiate this expression with respect to benefits (B). A sufficient condition for an increase in benefits to reduce unambiguously the transition rate from non-employment to employment is for the utility function to be linear in income.

Note, however, that (6) constrains a variable to have essentially the same coefficient in the transition rate from employment to nonemployment and in the transition rate from nonemployment to employment. This condition will be violated, for example, in the simple model defined by (5a′) through (5c′), where expanding Medicaid eligibility would only affect transitions from non-employment to employment and not vice-versa. Further, while we would expect changes in AFDC benefits to affect both transitions into employment and transitions out of employment, we may not expect the effects to be governed by a single coefficient. Thus we consider a more general model where we essentially interact lagged employment status with each explanatory variable. We assume that an individual who was employed last period is employed this period if

(7a) $$I^*_{eit} = Z_{eit}\gamma_e + u_{eit} > 0$$

Further, we assume that an individual who was not employed last period is not employed this period if

(7b) $$I^*_{neit} = Z_{neit}\gamma_{ne} + u_{neit} > 0$$

Finally, we must specify an equation for the initial period in our data to avoid selection bias in our estimation.[10] We assume that an individual is employed in the initial period if

(7c) $$I^*_{oi} = Z_{oi}\gamma_o + u_{oi} > 0.$$

[10] This is also true in the index function (6) that contains a dummy variable denoting last period's employment status.

One advantage of the above specification is that it allows us to measure the effect of AFDC benefits on transitions into non-employment. As noted above, the previous literature has focused almost exclusively on the effect on transitions out of non-employment.

To save space, we do not consider a general specification of the likelihood for this model. Instead, we only examine a simple example. In our work, we assume that each of the error terms in (7a) through (7c) follows an error components specification,

$$u_{ikt} = v_{ik} + \varepsilon_{ikt}\ ,\ k = e,\ ne,\ 0, \tag{8}$$

where 0 denotes the initial period,[11] and that each of the idiosyncratic error terms ε_{it} follow a logistic distribution.[12] Then the index functions in (7a) through (7c) define the following probabilities

$$P_{ik}(t \mid v_{ki}) = (1 + \exp(-Z_{ikt}\gamma_k - v_{ki}), \quad k = e,\ ne,\ 0. \tag{9}$$

Consider the following labor market history. The individual is not employed in the initial period. She makes a transition from non-employment to employment at time t1, and makes a transition from employment to non-employment at time t2. The last period observed is period T. Her contribution to the likelihood is given by (after dropping the i subscript for notational ease)

$$\begin{aligned} L = \int_v \left(1 - P_0(1 \mid v_0)\right) \prod_{j=1}^{t_1-1} \left(1 - P_{ne}(j \mid v_{ne})\right) \cdot P_{ne}(t_1 \mid v_{ne}) \\ \cdot \prod_{j=t1+1}^{t_2-1} \left(1 - P_e(j \mid v_e)\right) \cdot P_e(t_2 \mid v_e) \\ \cdot \prod_{j=t_2+1}^{T} \left(1 - p_{ne}(j \mid v_{ne})\right) dH(v_0,\ v_{ne},\ v_e) \end{aligned} \tag{10}$$

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[11]The t subscript is dropped when k=0 in (8) and (9).

[12]Alternatively, one could assume that they follow a normal distribution.

where $H(v_0,v_{ne},v_e)$ is the distribution function for the individual-specific errors. We will use the one factor model used by Ham and LaLonde (1996), as well as the approach of McCall (1996), to model $H(\cdot)$.

Note that the model (7a) to (7c) can be viewed as a estimating a duration model with no duration dependence in either transition rate. Thus, the steady-state probability of being employed in this model is given by

$$(11) \qquad P_e^* = \frac{P_e^{-1}}{P_e^{-1} + P_{ne}^{-1}} \, .$$

One may view the probit approach (1) as estimating the determinants of (11) directly. This raises the question of what we gain by estimating the transition probabilities from employment to non-employment (7a) and non-employment to employment (7b) separately, as opposed to simply estimating equation (11) directly. We would argue that there are several advantages to estimating the transition rates separately. First, if we are to understand *how* Medicaid expansions (and other explanatory variables) affect employment status (rather than viewing the mechanism as a black box), we need to understand how the expansions affect the different components determining employment status.[13] Second, examining entries and exits separately may be useful in policy design. For example, if the expansions aid entry into employment but do not reduce exits from

[13] In fact one may want to go further, and distinguish out of the labor force from in the labor force and looking for a job in the estimation.

employment, then policy makers may want to focus additional welfare reform efforts on strategies that reduce employment exits.[14]

III.3. A Simple Dynamic Participation Model with Duration Dependence

As noted above, our labor force participation model defined by (5a) through (5c) produces a model equivalent to a duration model with no duration dependence. Researchers working with duration data on disadvantaged women have found evidence of duration dependence, even after controlling for unobserved heterogeneity. To obtain a theoretical model which exhibits duration dependence, we modify our labor force participation model, again aiming for the simplest possible theoretical model that would produce this effect in the data. Specifically, we now assume that the arrival rate of job offers falls with the length of time that a person has been out of employment. Thus

$$\begin{aligned} \alpha_t &= \alpha(t),\ \alpha' < 0 \quad \textit{for}\ t < t_a \\ &= \bar{\alpha} \qquad\qquad\quad \textit{for}\ t \geq t_a \end{aligned} \tag{12a}$$

where t is the length of time non-employed in the current spell.[15] We also assume that the layoff rate out of employment, β, falls with the length of time in the current employment spell

$$\begin{aligned} \beta_t &= \beta(t),\ \beta' < 0 \quad \textit{for}\ t < t_b \\ &= \bar{\beta} \qquad\qquad\quad \textit{for}\ t \geq t_b \end{aligned} . \tag{12b}$$

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[14]An example is the National Supported Work training program, which appears to reduce the transition rate out of employment but does not affect the transition rate out of non-employment. This is in contrast to Job Training Partnership Act classroom training, which appears to affect only the transition rate out of non-employment. See Ham and LaLonde (1996) and Eberwein, Ham and LaLonde (1997) for details.

[15]We assume that the arrival rate becomes fixed after a certain point in order to induce stationarity into the model at some point.

In this model the value function for searching falls with the duration of the current non-employment spell. This is because the job offer arrival rate falls with current duration, and thus the transition rate out of non-employment must fall with length of time in the spell. Further, as one would expect, these modifications also lead to negative duration dependence in the transition rate out of employment.

Thus we next consider a duration model with duration dependence and unobserved heterogeneity.[16] Here we focus on time spent on welfare and off welfare, rather than time spent in employment, to make this section more comparable with previous research. (We discuss combining an analysis of both employment and welfare below.) In a data set such as the SIPP there are four types of welfare and non-welfare spells:

(i) spells on welfare in progress at the start of the sampling frame (interrupted welfare spells);

(ii) spells on welfare that begin after the start of the sampling frame (fresh welfare spells);

(iii) spells off welfare in progress at the start of the sampling frame (interrupted spells off welfare);

(iv) spells off welfare that begin after the start of the sampling frame (fresh spells off welfare).

As discussed above, previous research has focused on fresh welfare spells, omitting data on interrupted welfare spells and time spent off welfare. This has the advantage that one can obtain parameters of the hazard function for a new spell for a woman chosen at random, which would

[16]As a practical matter, allowing for duration dependence may be important since the Medicaid eligibility variables will be trending upward for most or all waves of SIPP, and they could also pick up duration dependence effects if we ignore them.

not generally be true if one combined data on fresh and interrupted spells to estimate a common set of parameters. However, it has the disadvantage that one will not see spell lengths of more than two or three years. By estimating a separate hazard for interrupted spells we can focus on long term welfare recipients also. Further, by jointly analyzing time in the spells i) through iv), we eliminate any selection bias in the estimates.

Researchers have defined a hazard function for leaving a fresh welfare spell in terms of variables describing the characteristics of the family and the mother X_{it}, variables that proxy AFDC generosity $AFDC_{nst}$,[17] and unemployment rates UR_{st}. We define a hazard function in terms of these variables as well as a vector of variables that proxy Medicaid eligibility Med_{nst}. Assuming a logit functional form, we have

(13a)
$$\lambda_w(r|\,.,\theta_w) = \frac{1}{1 + \exp(-(y_w(r\,|\,\theta_w)))}$$

where

(13b)
$$\begin{aligned} y_w(r\,|\,\theta_w) = h_w(r) + \gamma_{1w}X_{it} + \gamma_{2w}Med_{nst} + \gamma_{3w}AFDC_{nst} \\ +\gamma_{4w}UR_{st} + \theta_w \end{aligned}.$$

In equations (13a) and (13b), r represents the current duration of the fresh welfare spell and θ_w represents an unobserved heterogeneity component. Previous researchers have not analyzed interrupted spells since deriving the appropriate density function for time remaining in an interrupted spell in terms of the parameters of (13a) and (13b) is extremely complicated in the

[17]One advantage of our approach is that we can incorporate the fact that the implicit tax rate on earnings above deductions is approximately 100% after 4 months of being on welfare. We intend to do this in future work.

presence of unobserved heterogeneity.[18] However the interrupted spells are likely to contain important information on long term welfare recipients, particularly in a relatively short panel such as SIPP, and thus it is quite desirable to analyze these spells. To do this, we follow the pragmatic suggestion of Heckman and Singer (1984) and specify a separate hazard function and heterogeneity term for spells in progress at the start of the sampling period

$$\lambda_{w'}(r' \mid \theta_{w'}) = \frac{1}{1 + \exp(-(y_{w'}(r' \mid \theta_{w'})))}. \qquad (14)$$

In (14), r' represents the length of time since the start of the sample, w' denotes an interrupted spell, and the argument is along the same lines as (13b) with different parameters. We emphasize that this is only an approximate solution to the problems created by left censoring, but it does allow us to utilize data on interrupted spells.[19]

As noted above we will also analyze spells off welfare. There are two reasons such spells should be analyzed. First, it allows us to investigate whether welfare benefit levels or Medicaid eligibility affect transitions into welfare. Such entry effects could be important if, for example, preventing initial entry into welfare has long-run consequences for welfare participation. Second, if the hazard functions for entering welfare depend on unobserved heterogeneity terms which are correlated with the unobserved heterogeneity terms in the hazard functions for leaving welfare, there is the possibility of selection bias if one only analyzes time spent on welfare

[18] Calculating this contribution is straightforward if there is no unobserved heterogeneity and the start date of the spell is known.

[19] Although this approach has not been used to analyze welfare spells, Ham and LaLonde (1996) and Eberwein, Ham, and LaLonde (1997) use this approach to analyze the effect of being offered or receiving training on transitions between employment and nonemployment of disadvantaged women.

(Heckman and Singer 1984). For example, suppose expanded Medicaid eligibility reduces the probability of an individual entering welfare. Then those who enter welfare when they face high Medicaid eligibility standards will be those with a high heterogeneity term (for leaving time spent off welfare) and, under standard assumptions, will have an unobserved heterogeneity term that makes it less likely that they leave a fresh spell on welfare. This will create a negative correlation between Medicaid eligibility and the unobserved heterogeneity in the hazard function for leaving a fresh spell of welfare. [20] We specify similar hazard functions for time spent in interrupted and fresh spells off welfare to those for time spent on welfare. We will jointly estimate the parameters of the hazard functions for the interrupted and fresh spells on and off welfare, maximizing the appropriate likelihood function while allowing the unobserved heterogeneity terms to be correlated across the spells. Note that several of the explanatory variables, (e.g. welfare and Medicaid values or income limits, family size and state unemployment rates) change with time and thus help to identify the parameters of the joint likelihood. Our use of the time-changing variables gives us an exclusion restriction in the sense that the values of these variables from the interrupted spells affect the fresh spells only through the selection process. Thus, they help control for the selection bias in terms of the fresh spells discussed above. Since this type of model has been estimated for disadvantaged women by, e.g.,

[20] See Appendix 2 of Eberwein, Ham, and LaLonde 1997 for a detailed discussion of this issue. Note that we are not focusing on the bias that occurs (even with random assignment) within a spell because of unobserved heterogeneity (Ridder and Verbakel 1984).

Ham and LaLonde (1996) and Eberwein, Ham and LaLonde (1997), we omit describing the likelihood function here.[21]

III.4. Analyzing Welfare Status and Employment Status Jointly

Until now we have followed the literature and treated i) non-employment and ii) welfare receipt as essentially synonymous; we have also treated iii) employment and iv) off-welfare as synonymous. As noted above we intend to estimate each of the above models first specifying the respective dependent variable in terms of employment/non-employment and then specifying it in terms of on-welfare/off-welfare. However, many individuals who are not employed are not on welfare, and as previous researchers have noted (see, e.g. Engberg, Gottschalk, and Wolf 1990), a substantial number of individuals on welfare are also employed, so that it is useful to analyze welfare participation and employment status jointly. One possibility would be to estimate each of the above models jointly; for example in the case of the random effects probit specification, we could estimate a bivariate probit model in terms of welfare status and employment status. This would lead to a potential increase in efficiency as compared to separate estimation. On the other hand, many of the models already involve relatively complex estimation, and this new estimation approach will make things significantly harder. There are two straightforward ways in which we can address this problem. First we can estimate the models separately and then

[21] These papers were concerned with the effect of training on employment histories, and did not consider the effect of AFDC benefits or Medicaid on such histories. An additional difference between our approach and these studies is that we will also estimate an equation along the lines of (7a) to describe the initial state, since this will be helpful in performing simulations of long-run and short-run effects. (These earlier studies could not separately identify the parameters determining the initial state in their data.) In our work we will let the initial state depend on demand conditions before the start of the sample period, while the transition rates out of the current and lagged spells will depend on current demand conditions. The timing of the demand conditions gives us an exclusion restriction which will help identify the model.

simulate them jointly, examining the short-run, medium run and long-run probabilities of the effect of AFDC changes and Medicaid expansions on the probability that an individual is: i) off-welfare and in employment, ii) on welfare and in employment, iii) on welfare and not employed, and iv) off welfare and not employed.[22] Secondly, in the models defined by (9) and (10) and by (13a) and (14), we will also look at the effect of the Medicaid expansions on specific transitions from i) on welfare to employment off welfare and ii) off welfare and in employment to on welfare, since we would expect the Medicaid expansions to have their biggest effects in these cases.[23]

III.5. Important Statistical Issues: Model Fit, Seam Bias, and Spurious Transitions

For each of the models we face at least three additional issues. First, how well do the models fit the data? One approach to testing the fit of the model is to save some data (either the last few months of a given wave or one entire wave) and examine both the in-sample and out-of-sample performance. Here we would simulate the model and use goodness-of-fit statistics (e.g., Heckman and Walker 1990). This would not only help us to understand the predicted short-run and medium-run dynamics for each model, but would also help us to compare the performance of

[22] We face the issue that estimating welfare status and employment status separately will not allow us to recover the joint distribution of the unobservables, which would be helpful in estimation. In some cases, we can recover the joint distribution after separate estimation (see, e.g., Chamberlain 1984), just as one does in the calculating the covariance matrix in a seemingly unrelated regression. In the more complicated models we will have to ignore any correlation between the unobservables. This generally will not lead to inconsistency, but will involve a loss of efficiency in simulation.

[23]We can also examine other specific transitions of policy interest, such as employment on welfare to employment off welfare.

the different models. Carrying out these simulations is relatively straightforward; see e.g. Eberwein, Ham and LaLonde (1997).

A second issue we must face in each model is that of "seam bias." Individuals are interviewed in every four months in the SIPP, and Census Bureau researchers have shown that there are a disproportionate number of transitions in the fourth (interview) month. The approach to this problem that has been used in the past is to use index functions or transition rates that apply to the four month period covered by the interview. However, this approach has the disadvantage that a discrete time model cannot really handle an interval shorter than that for which the index function is defined (see Flinn and Heckman 1982) and a four month interval can be quite long when considering transitions in and out of employment. In addition, information on the timing of transitions that reportedly occurred in months other than the seam month is lost.

We plan to take a different approach and treat seam bias as a censoring problem given our monthly data. Consider the probit model defined by (1) and the following employment history. An individual is employed at the beginning of the sample period and stays employed up to period t_1, at which point she enters non-employment and stays there for the remainder of the sample period. For simplicity, assume that t_1 is the first month of the four month period, and thus within the four month interval $I_1 = 0$, $I_2 = 0$, $I_3 = 0$, $I_4 = 0$, where I_j is an indicator function equal to 1 if the individual is employed in the jth month in the interval and zero otherwise. Denote L_1 as the likelihood for the case that the data are correct. Next define L_2 as the likelihood for the case where she really makes the transition into month 2, i.e. the true data are $I_1 = 1$, $I_2 = 0$, $I_3 = 0$, $I_4 = 0$. Similarly let L_3 denote the likelihood for the case where the true data are $I_1 = 1$, $I_2 = 1$, $I_3 =$

0, $I_4 = 0$, and define L_4 in a similar fashion. Then one approach to seam bias is to use the following as the contribution for each person to the likelihood function:

$$L^*=(L_1 + L_2 + L_3 + L_4)/4 \quad (15)$$

In this procedure we would use (15) regardless of which of the four months in the interval a transition was reported to have taken place. Alternatively, we could make this adjustment only if the transition is reported to have occurred in the last month in the interval, since seam bias captures the idea that transitions in the earlier months in the interval are attributed to the last month. If we make the adjustment only in the last month, we may also want to estimate the weights in (15) on each term rather than imposing a weight of one quarter.

Further, one could test for seam bias by comparing estimates based on the likelihood (15) with estimates based on the probit model using the reported data and a Hausman (1978) test. Under the null hypothesis of no seam bias, estimates based on the standard likelihood are efficient, while those based on (15) are consistent but inefficient. As a further test of the robustness of our results, we will use both the method we propose and the previously-used method of using only one observation per interview period and examine whether and how our conclusions are affected. Finally, if an individual has more than one transition, we would need to extend this procedure. This extension is straightforward but notationally cumbersome and we omit it to save space. The approach also is easily transferable to the duration models or to the index function with the lagged dependent variable.

A third problem we face is the possibility that our results may be driven by spurious transitions where an individual is, for example, erroneously coded as employed in a given period when in fact she is not employed in that period, and is not employed in the preceding or following periods. One would suspect that the duration models might be especially sensitive to this problem, since this type of coding error would to a spurious transition out of non-employment and a spurious very short employment spell. We will address this issue by recoding the data to eliminate any spells of one month duration, and compare the results to the original data. Interestingly, for the duration models we have estimated so far (see the discussion of preliminary results below), this change in coding makes no substantive difference in our results.

In this version of the paper we focus first on the specific transition rate from employment off welfare to welfare and the specific transition rate for welfare to employment off welfare, using both interrupted and fresh spells. We next focus on all transitions off welfare, again using fresh and interrupted spells. Finally we consider all exits from employment and all exits from non-employment, using only interrupted spells. We ignore unobserved heterogeneity in the current version of the paper and estimate all transitions separately rather than estimating them jointly. We will estimate the more general model in future versions of the paper.

IV. Data

Our data consist of a sample of spells of single motherhood for 15,998 women between the ages of 18 and 55 drawn from the 1987, 1988, 1990, 1991, 1992, and 1993 panels of the SIPP. The six panels we use cover the period from October 1986 to December 1995, which was the period during which Medicaid eligibility expanded most rapidly. Each panel of the SIPP is composed of four rotation groups which are interviewed three times a year about experiences over the preceding four months, providing up to 28 months of data for the 1987 panel, 24 months for the 1988 panel, 32 months for 1990 and 1991, 40 months for 1992, and 36 months for 1993.

At each interview participants were asked about their experiences over the previous four months, including questions about monthly changes in family composition, employment and participation in cash transfer programs. In addition, the SIPP contains demographic information such as age, education, and state of residence.[24]

We define a single mother as a currently unmarried woman caring for at least one child, where a child is defined as an individual younger than age 18, or between 18 and 23 and a full-time student. For women who are not single mothers during all months of the data, only the months of single motherhood are included in our sample. From these spells of single motherhood we identify time spent participating in welfare, time spent off welfare, time spent in employment and time spent in non-employment.[25] Women who are both employed and on welfare are counted as participating in welfare when examining transitions involving welfare, and are counted as being employed when examining transitions out of employment without regard to welfare.[26]

The bottom panel of Table 1A shows the number of welfare spells of each type (interrupted and fresh) present in the data. There are 3498 spells of welfare in progress at the start of the sample. Of these spells, fewer than half (1612) of them show a transition, with 943 of the transitions being to employment. Comparing spells in progress at the beginning of the

[24] To preserve confidentiality, the Census Bureau does not identify the state of residence for individuals in low-population states. Since our empirical strategy requires information about state of residence, only individuals in the 42 uniquely identified states are used.

[25] An AFDC participant is considered to have made a transition from welfare to employment if she exits welfare and if in either the same month or the following month she reports being employed. If she exits welfare and does not become employed, the spell is treated as "censored" for the purpose of estimating the transition intensity from welfare to employment.

[26] Approximately 3.3 percent of the 301,594 person-months in the data are months of both AFDC participation and employment.

sample with fresh spells, the fresh spells are shorter on average and are more likely to end with a transition to employment. (Duration for the spells in progress is measured from the start of the sample.) This difference is not surprising, as women who begin the sample on AFDC are more likely to be long-term AFDC participants than women whose spell starts during the sample (i.e. have unobserved heterogeneity that makes them more likely to stay on welfare) or because of negative duration dependence.

The rest of Table 1A shows the means of the variables we use in our analysis, as of the first month of the welfare participation spell. The demographic variables include the woman's age, the highest grade she completed, whether she is non-white, the number of children she has, the number of her children who are under six years old, the age of her youngest child, and whether she is divorced, separated, or widowed (the omitted category is never married). From the table, it appears that women with a spell in progress at the start of the sample are likely to be slightly younger, to have completed fewer years of education, are more likely to be non-white, and to have more children, particularly young children, than women who have a spell start during the sample.

Table 1B gives the same information for spells of employment off welfare, and employment and non-employment without regard to welfare. Not surprisingly the values of the demographic variables for women in the first month of a nonemployment spell are similar to the values for women in the first month of a welfare spell. However women in employment spells are older, have completed more education, are less likely to be non-white, have fewer children, and are more likely to be divorced than women in welfare spells.

Using the state of residence information available in the SIPP, we link information from other sources to our data, including the monthly unemployment rate in the state,[27] the level of the minimum wage in the state,[28] and the state AFDC and Medicaid eligibility standards. We use the state unemployment rate to proxy economic conditions women face, since during economic downturns women will be less likely to exit welfare and more likely to enter it. The minimum wage and the AFDC and Medicaid eligibility standards are used to distinguish the women affected by the Medicaid expansions.

To identify the effect of the Medicaid expansions, we use the fact that the expansions affected women differently depending on their state of residence, the size of their family, the age of their children, and the year.[29] The Medicaid expansions took place over several years and were implemented as phased-in federal mandates with optional provisions that states could enact. The phasing-in was done by age, with younger children becoming eligible sooner. In addition, eligibility standards were more lenient for younger children. For example, consider a woman with two children, an infant and a five-year old, living in Alabama or North Carolina. Neither, one, or both of her children are eligible according to the following standards for her family income:

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[27]These data were obtained from the Bureau of Labor Statistics website: http://stats.bls.gov/top20.html.

[28]We are grateful to David Neumark for providing us with the minimum wage data.

[29]This identification strategy has been used previously by (among others) Currie and Gruber (1996), Cutler and Gruber (1996), Shore-Sheppard (1997), and Yelowitz (1995).

	1988	1990	1992
Alabama	before July: neither eligible after July: infant if < 100% of poverty	before April: infant if < 100% of poverty after April: infant if < 133% of poverty	infant if < 133% of poverty 5 yr old if < 100% of poverty
North Carolina	infant if < 100% of poverty	infant if < 150% of poverty 5 yr old if < 100% of poverty	infant if < 185% of poverty 5 yr old if < 100% of poverty

This table illustrates that some women who are contemplating leaving AFDC will have some of their children eligible for Medicaid, while others have none of their children eligible and still others have all of their children eligible.

The income levels also vary relative to the AFDC eligibility level in the state. In states which have very generous income cutoffs for AFDC eligibility, the expanded eligibility limits for Medicaid represent a relatively smaller change in eligibility limits, while in states which have very strict income standards for AFDC, the expansions produce a relatively large increase in the eligibility limits for Medicaid. We attempt to capture this variation in several ways in our analysis. First, since the youngest child in a family is the most likely to be eligible under the expansions, we create variables which capture variation in eligibility for the youngest child. One such variable is the amount of money a woman could earn per month and still have her youngest child be eligible for Medicaid. This Medicaid income limit depends on the age of the youngest child, the state of residence of the family, the month, and the size of the family, since the legislated Medicaid income limits are in the form of a percent of the Federal poverty line, which differs by family size.[30] We calculate the AFDC income limit for the woman, which is a function of the size of the woman's family, the state AFDC need and payment standards, and the child care and earnings disregards in effect at that time. The Medicaid income limit for the youngest child variable is thus measured as the maximum of the AFDC income limit and the Medicaid income limit. We include both it and the AFDC income limit in our analysis.[31] Another variable we create is the fraction of the woman's children who are eligible for Medicaid only under the expansions (in that month) according to their age. Thus a child would be considered age-eligible in a month if there was a legislated expansion in place for that age child, regardless of the income limit accompanying that expansion. Our final Medicaid variable is the fraction of a woman's children who would be eligible for Medicaid coverage if she worked 40 hours a week at the minimum wage.[32] This variable takes advantage of additional variation in state Medicaid expansion levels and state minimum wage levels as well as the previously discussed variation. Both of these last two variables are intended to account for the fact that women who have a larger fraction of their children who could be covered by Medicaid independent of AFDC are more likely to respond to the expansions than women who have a relatively small fraction of their children eligible since the value of Medicaid coverage under the expansions is relatively higher for such women.

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[30]In the analysis which follows, we also tried using the Medicaid income limit as a percent of the poverty line, but there was no difference in the results.

[31]This specification is similar to the variable used by Yelowitz (1995) but is less restrictive in the sense that he constrains the variables to have coefficients which are equal in absolute value but are different in sign. In general, this constraint is not satisfied in our data.

[32]We also tried 30 hours, however there was no difference in the results.

We show the variation in these AFDC and Medicaid variables in Table 2. As expected, all of the Medicaid variables show substantial increases over the time period, particularly between 1990 and 1993. The AFDC income limit also increases, although between 1991 and 1994 the limit increases very little. The fraction of children age-eligible and the fraction who are eligible if the mother works 40 hours a week at the minimum wage are virtually identical, indicating that the income expansion levels are greater than a minimum-wage income for most ages. The values of these variables for the women with interrupted and fresh welfare spells are shown at the bottom of Table 1A. Unsurprisingly, the AFDC income limit is higher for women with interrupted spells. The Medicaid variables are slightly higher among women with spells in progress at the start of the sample, however the difference is quite small.

V. Results

Our estimates of the probability of leaving welfare for employment for the interrupted spells (in progress at the start of the sampling frame) are contained in columns (1) through (6) of Table 3A. As noted above, this sample will contain the majority of the long term welfare recipients, and thus is of particular interest for policy. To the best of our knowledge, this is the first duration study to focus on long-term recipients in this manner. In each specification, we include the AFDC income limit to control for variation in AFDC eligibility that will affect the likelihood a woman exits welfare. In addition, each specification includes one of the Medicaid variables discussed above. We estimate each specification with and without year effects (the results with year effects are in the second column of each pair). Columns (1) and (2) contain the results using the maximum of the state Medicaid income limit for the youngest child and the

AFDC income limit as the measure of Medicaid generosity. In columns (3) and (4) we present the results, with and without year dummies, from a specification including the fraction of children eligible if the mother works 40 hours a week at the minimum wage, while in columns (5) and (6) we use the fraction of children age-eligible under the expansions.

To determine our specification of the duration dependence, we use the Schwartz criterion (see, e.g., Judge *et al.* 1980, pp. 425-426) to choose the level of the polynomial in log duration. We use this criterion since it will lead to a more parsimonious specification of duration dependence than the more standard likelihood ratio test, and in their monte carlo results, Baker and Melino (1997) found that over-fitting duration dependence leads to small sample bias in the parameter estimates. On this basis, we use a fourth order polynomial in duration dependence.[33] For comparability, we use the level of duration dependence with time dummies that we chose when omitting the time dummies.

The coefficients on the control variables change very little across specifications. There appears to be a nonlinear relationship between age and the probability of leaving welfare for employment, with the probability declining with age to a minimum around age 42, then increasing. Being non-white and having more children (particularly children under 6) significantly lowers the probability of leaving welfare for employment, while having more education and being divorced, separated, or widowed (as compared to never married) increases the probability. Controlling for the number of children and the number less than six years old, the age of the youngest child does not appear to affect the likelihood of moving from welfare to

[33]Recall that duration is measured from the start of the sampling period. In future work we will also consider using total duration (from the beginning of the spell) instead. However, to obtain this variable we must obtain additional data and thus it is not available for this draft.

work, while the probability of leaving declines significantly with the state unemployment rate. Higher AFDC income limits significantly lower the probability of leaving welfare for a job, as expected.

If the Medicaid expansions increase transitions from welfare to employment, as hypothesized, the coefficients on the Medicaid variables should be positive. With the exception of the Medicaid income limit in the specification with year dummies, the coefficients are indeed positive, however only the variables measuring the fraction of the woman's children who are eligible are significant, and only in the specifications without controls for year. The year controls are intended to capture unmeasured changes in the macroeconomy or national policy over time that might affect the likelihood that a woman leaves welfare for employment. If the unemployment rate successfully captures such changes, including the year dummies may merely absorb some of the variation in the Medicaid variables, leading to small and insignificant estimates of the effects of Medicaid expansions. However if the year dummies are picking up important macroeconomic variation affecting welfare participation and employment and hence belong in the equation, then the effect of expanded Medicaid eligibility on transitions from welfare to employment appears to be small and insignificant. In future work we will add more measures of demand shocks at the national level when we exclude year dummies.

Table 3B contains our empirical results estimating transitions to employment (off welfare) using welfare spells that begin after the start of the sample period. As noted above, this sample is likely to contain many more short-term welfare participants. The format and the explanatory variables are identical to that of Table 3A. There are several differences in the results, however. First, and most important, the fraction of children eligible for Medicaid no longer has a significant effect on the probability of exiting welfare for employment, even in the specification without year effects, and including the year effects actually results in a negative sign (although the coefficient is not statistically significant). Second, several of the variables, including age, race, number of children, marital status, and the AFDC income limit are either insignificant or only marginally significant, although all have the same signs as in Table 3A. However education, the number of children less than six years old, and the unemployment rate have similar effects in both tables.

Tables 4A and 4B show the coefficients from hazards of exiting welfare without regard to employment for interrupted and fresh spells, respectively. (A woman may exit welfare for a state other than employment through marriage or by receiving an increase in other income, for example.) The results in Table 4A are quite similar to those from the exit to employment hazards, although several of the coefficients are smaller in magnitude. The Medicaid variables show a similar pattern for both spells, with the variables measuring the fraction eligible having positive coefficients that are significant only when year dummies are not included. The coefficients from the fresh spells (Table 4B) are also similar to those from the exit to employment hazards using fresh spells (Table 3B), although many of the coefficients in Table 4B are smaller and few are statistically significant.

Employment and non-employment spells are considered in Tables 5, 6, and 7. In Table 5 we look at welfare entry effects: how does expanded Medicaid eligibility affect the likelihood a woman leaves employment for welfare? For the most part the results are the opposite of those for welfare exit in Tables 3 and 4, with the primary exception being the coefficient on the AFDC income limit, which is small and not statistically significant in any specification. Most of the

Medicaid variables are negative, as would be expected if the availability of Medicaid retarded entry into welfare, however the coefficients are never significant. The control variables have the expected sign, however, and are all statistically significant except for the variables for the number of children younger than six and the dummy for widow.

Tables 6 and 7 show our results from employment and non-employment exit hazards. Not surprisingly the coefficients on the control variables are of opposite signs, and most are significant for both hazards. The principal point of deviation from this pattern is in the AFDC income limit variable, which appears to have no effect on exits from employment, but to have a significantly negative effect on exits from nonemployment (indicating that higher AFDC income limits lead to a lower probability of exit from non-employment). In Table 6 the Medicaid variables tend to have the negative sign predicted by theory only in the specifications with the year effects, contrary to the results of previous tables, however once again the coefficients are very rarely significant. The signs of the Medicaid variables are consistently positive in Table 7 (with one exception), however they are again only significant when year variables are not included.

Overall, the results presented above provide some evidence that expanded Medicaid eligibility leads single mothers to exit welfare more quickly, however the effects are not robust to the inclusion of year dummies and tend to be limited to the population of women who began the sample on welfare. This conclusion is somewhat surprising, given that previous research (Yelowitz 1995) found a strong and robust relationship between expanded Medicaid eligibility and increased labor force participation (and reduced welfare participation). As a robustness check and to more easily compare our results and previous studies which used cross-sectional data, we estimate simple logits of AFDC participation and employment using our SIPP data (accounting for the fact that we have repeated observations of the same individual in the calculation of the standard errors). We find results which are essentially the same as those that we obtain from the hazard models (see Tables 8 and 9). Among women who began the sample on AFDC, the estimated effects of the Medicaid expansions are the expected sign and are significant except when year dummies are added to the specification. Among women who did not begin the sample on AFDC, we find very little evidence of an effect of Medicaid eligibility, with the estimated effects almost never being significant and often having the opposite sign from the expected one. When the two samples are pooled, the larger size of the sample without interrupted spells (221,806 person-months as compared to 79,788 person-months) leads to estimates which mimic the estimates for women who did not start the sample on AFDC: the expansions appear to have had little effect on the overall sample.[34]

VI. Conclusions and Future Work

In this paper we lay out a framework to explore the impact of expanded public health insurance coverage for children on transitions between welfare and work using a monthly hazard rate model and data from the Survey of Income and Program Participation. In this version of the paper we estimate separate hazards for transitions into and out of employment and welfare, estimating models for both interrupted and fresh spells for the case where there is no unobserved heterogeneity in the hazard function. We find some evidence that expanded Medicaid eligibility

[34]While these results differ from the results of Yelowitz (1995), they are similar to the results of Meyer and Rosenbaum (1998) who include measures of Medicaid in estimates of the employment probability of single women.

for children leads single mothers to exit welfare more quickly, however the effects are not robust to the inclusion of year effects. In addition, the effect appears to be strongest and most consistent among long-term recipients (as proxied by recipients who begin the sample on welfare). We find less evidence of an effect of expanded Medicaid eligibility on transitions into welfare. A somewhat surprising finding is that higher AFDC income limits appear to have little effect on the probability of such transitions out of employment or time spent off welfare. To the best of our knowledge, this is one of the first papers to examine welfare spells for women who began the sample on welfare. These women are more likely to consist of long-term recipients, which is precisely the group of welfare recipients on which current welfare policy is focused.

Clearly this research is a work-in-progress. We are currently working on improving and refining our analysis in several ways. First, we plan to estimate the model accounting for unobserved heterogeneity and incorporating alternative solutions to the seam bias problem in the SIPP data. Second, we are exploring alternative ways of parameterizing AFDC and Medicaid eligibility and generosity in order to capture more fully which women were affected most strongly by the expansions while controlling for the effects of the AFDC program. Finally, we are incorporating information from the SIPP topical modules on health and disability status (to account for the fact that women who are unwell or disabled are less likely to exit AFDC) and the start date of the current welfare spell (to improve our treatment of the interrupted spells).

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Table 1A: Means at First Month of Spell: Exits from Welfare

	Welfare to Employment		Welfare Ignoring Employment	
Spell:	In Progress At Start	Begins After Start	In Progress At Start	Begins After Start
Age	28.802	30.114	28.802	30.114
	(0.135)	(0.188)	(0.135)	(0.188)
Age ^{2}	893.441	974.569	893.441	974.569
	(8.628)	(12.364)	(8.628)	(12.364)
Highest Grade Completed	10.968	11.128	10.968	11.128
	(0.038)	(0.060)	(0.038)	(0.060)
Non-White	0.440	0.406	0.440	0.406
	(0.008)	(0.011)	(0.008)	(0.011)
Number of Children < 6	1.021	0.824	1.021	0.824
Years Old	(0.015)	(0.019)	(0.015)	(0.019)
Age of Youngest Child	4.174	5.145	4.174	5.145
	(0.076)	(0.106)	(0.076)	(0.106)
Number of Children	2.039	1.890	2.039	1.890
	(0.020)	(0.024)	(0.020)	(0.024)
Divorced	0.239	0.287	0.239	0.287
	(0.007)	(0.010)	(0.007)	(0.010)
Separated	0.204	0.212	0.204	0.212
	(0.007)	(0.009)	(0.007)	(0.009)
Widowed	0.022	0.027	0.022	0.027
	(0.002)	(0.004)	(0.002)	(0.004)
Unemployment Rate	6.621	6.649	6.621	6.649
	(0.028)	(0.036)	(0.028)	(0.036)
AFDC Income Limit	1229.47	1142.82	1229.47	1142.82
(First 4 Months)	(7.467)	(9.633)	(7.467)	(9.633)
Medicaid Income Limit for	1607.46	1601.72	1607.46	1601.72
Youngest Child (Maximum)	(12.686)	(17.557)	(12.686)	(17.557)
Fraction of Children Age-	0.523	0.576	0.523	0.576
Eligible Under Expansions	(0.008)	(0.010)	(0.008)	(0.010)
Fraction of Children Eligible if	0.523	0.576	0.523	0.576
Mom Works 40 hrs/wk at Min.	(0.008)	(0.010)	(0.008)	(0.010)
Total Number of Spells	3498	1923	3498	1923
Number With No Transition	2555	1163	1886	931
Number With a Transition	943	760	1612	992
Mean Duration of Spells	16.638	8.878	16.579	8.788
(Months)	(0.205)	(0.178)	(0.206)	(0.179)
Mean Duration of Spells	17.845	9.942	21.106	11.556
With No Transition (Months)	(0.247)	(0.251)	(0.297)	(0.300)
Mean Duration of Spells	13.367	7.249	11.282	6.191
With a Transition (Months)	(0.340)	(0.222)	(0.214)	(0.163)

Table 1B: Means at First Month of Spell: Other Exits

	Employment-Off-Welfare to Welfare	Empl to Non-Empl Ignoring Welfare	Non-Empl to Empl Ignoring Welfare
Age	34.509	34.334	29.559
	(0.092)	(0.091)	(0.115)
Age ^{2}	1261.230	1249.920	951.821
	(6.482)	(6.350)	(7.505)
Highest Grade Completed	12.656	12.607	11.153
	(0.027)	(0.026)	(0.032)
Non-White	0.270	0.276	0.368
	(0.005)	(0.005)	(0.006)
Number of Children < 6	0.455	0.471	0.905
Years Old	(0.007)	(0.007)	(0.011)
Age of Youngest Child	8.586	8.433	4.841
	(0.068)	(0.066)	(0.069)
Number of Children	1.559	1.574	1.856
	(0.009)	(0.009)	(0.014)
Divorced	0.465	0.460	0.244
	(0.005)	(0.005)	(0.006)
Separated	0.245	0.245	0.226
	(0.005)	(0.005)	(0.005)
Widowed	0.056	0.054	0.054
	(0.003)	(0.002)	(0.003)
Unemployment Rate	6.384	6.391	6.601
	(0.018)	(0.017)	(0.021)
AFDC Income Limit	982.14	991.13	1152.08
(First 4 Months)	(3.931)	(3.897)	(5.560)
Medicaid Income Limit for	1197.64	1212.41	1522.83
Youngest Child (Maximum)	(6.605)	(6.540)	(9.498)
Fraction of Children Age-	0.328	0.336	0.513
Eligible Under Expansions	(0.005)	(0.005)	(0.006)
Fraction of Children Eligible if	0.327	0.334	0.513
Mom Works 40 hrs/wk at Min.	(0.005)	(0.005)	(0.006)
Total Number of Spells	8245	8638	5920
Number With No Transition	7856	5762	3900
Number With a Transition	389	2876	2020
Mean Duration of Spells	15.689	15.724	14.175
(Months)	(0.132)	(0.130)	(0.153)
Mean Duration of Spells	16.056	18.785	17.118
With No Transition (Months)	(0.136)	(0.166)	(0.197)
Mean Duration of Spells	8.283	9.589	8.493
With a Transition (Months)	(0.390)	(0.147)	(0.176)

Note: All transitions are for spells in progress at start of sample.

Table 2: Means of AFDC and Medicaid Eligibility Variables by Year

	1987	1988	1989	1990	1991	1992	1993	1994	1995
AFDC Income Limit (in $)	793.99	845.67	924.00	1042.72	1113.67	1116.98	1150.23	1171.53	1204.75
Medicaid Income Limit for Youngest Child (in $: = Max. of AFDC income limit and Medicaid limit)	793.99	847.80	944.47	1106.38	1314.90	1447.65	1737.35	1867.63	2055.34
Fraction of Children Age-Eligible	0	0.021	0.082	0.155	0.360	0.487	0.610	0.679	0.736
Fraction of Children Eligible if Mom Works 40 hrs/wk at Minimum Wage	0	0.020	0.081	0.155	0.360	0.487	0.610	0.679	0.736

Notes: Means calculated for all single mothers in sample as of January of the year indicated. All variables are calculated at the monthly level. Income limits are in real (1981-1983) dollars.

Table 3A: Estimated Coefficients from the Hazard Model
Transition from Welfare to Employment: Welfare Spells In Progress At Start

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.138	-0.123	-0.131	-0.122	-0.131	-0.122
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Age ^{2} * 10^{-3}	1.650	1.450	1.570	1.440	1.570	1.440
	(0.460)	(0.462)	(0.462)	(0.463)	(0.462)	(0.463)
Highest Grade Completed	0.072	0.070	0.071	0.070	0.071	0.070
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Non-White	-0.148	-0.147	-0.146	-0.140	-0.146	-0.140
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Number of Children < 6 Years Old	-0.284	-0.258	-0.284	-0.263	-0.284	-0.263
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Age of Youngest Child	-0.006	-0.009	0.001	-0.003	0.001	-0.003
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Number of Children	-0.083	-0.052	-0.053	-0.063	-0.052	-0.063
	(0.043)	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)
Divorced	0.541	0.527	0.539	0.530	0.539	0.530
	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)
Separated	0.438	0.418	0.438	0.421	0.439	0.421
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)
Widowed	0.551	0.522	0.551	0.526	0.551	0.526
	(0.237)	(0.237)	(0.238)	(0.237)	(0.238)	(0.237)
Unemployment Rate	-0.086	-0.099	-0.093	-0.099	-0.093	-0.099
	(0.022)	(0.024)	(0.022)	(0.024)	(0.022)	(0.024)
AFDC Income Limit * 10^{-3} (First Four Months)	-0.330	-0.260	-0.340	-0.340	-0.340	-0.340
	(0.129)	(0.131)	(0.110)	(0.112)	(0.110)	(0.112)
Medicaid Income Limit * 10^{-3} for Youngest Child (Maximum)	0.040	-0.090				
	(0.068)	(0.084)				
Fraction of Children Eligible if Mom Works 40 hrs/wk at Min.			0.216	0.053		
			(0.097)	(0.126)		
Fraction of Children Age-Eligible Under Expansions					0.221	0.061
					(0.097)	(0.126)
Log Duration	-1.272	-1.274	-1.228	-1.262	-1.227	-1.261
	(0.606)	(0.610)	(0.606)	(0.609)	(0.606)	(0.609)
(Log Duration)^{2}	3.238	3.309	3.169	3.300	3.166	3.299
	(0.697)	(0.708)	(0.697)	(0.708)	(0.697)	(0.708)
(Log Duration)^{3} * 10^{-1}	-17.374	-17.606	-17.038	-17.578	-17.028	-17.575
	(2.853)	(2.928)	(2.858)	(2.928)	(2.858)	(2.928)
(Log Duration)^{4} * 10^{-2}	26.922	26.811	26.376	26.781	26.361	26.778
	(3.823)	(3.957)	(3.831)	(3.956)	(3.831)	(3.956)
Log Likelihood	-4658.5	-4634.1	-4656.2	-4634.6	-4656.1	-4634.6
Time Dummies	N	Y	N	Y	N	Y

Note: Standard errors in parentheses. All equations include a constant (not reported).

Table 3B: Estimated Coefficients from the Hazard Model
Transition from Welfare to Employment: Welfare Spells Beginning After Start of Sample

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Age	-0.039	-0.031	-0.037	-0.032	-0.037	-0.032
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Age ^{2} * 10^{-3}	0.355	0.206	0.332	0.216	0.330	0.212
	(0.501)	(0.506)	(0.502)	(0.507)	(0.502)	(0.507)
Highest Grade Completed	0.088	0.084	0.086	0.085	0.086	0.085
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Non-White	-0.070	-0.061	-0.072	-0.063	-0.072	-0.063
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
Number of Children < 6	-0.255	-0.232	-0.255	-0.228	-0.255	-0.228
years old	(0.079)	(0.080)	(0.079)	(0.080)	(0.079)	(0.080)
Age of Youngest Child	0.022	0.014	0.026	0.013	0.026	0.013
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Number of Children	0.044	0.078	0.063	0.046	0.064	0.047
	(0.046)	(0.048)	(0.046)	(0.047)	(0.046)	(0.047)
Divorced	0.198	0.202	0.201	0.195	0.201	0.195
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Separated	0.196	0.200	0.200	0.194	0.200	0.194
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
Widowed	0.129	0.178	0.139	0.177	0.140	0.177
	(0.249)	(0.250)	(0.249)	(0.250)	(0.249)	(0.250)
Unemployment Rate	-0.086	-0.050	-0.086	-0.051	-0.086	-0.051
	(0.025)	(0.028)	(0.025)	(0.028)	(0.025)	(0.028)
AFDC Income Limit * 10^{-3}	-0.160	-0.130	-0.170	-0.220	-0.180	-0.220
(First Four Months)	(0.152)	(0.154)	(0.127)	(0.128)	(0.127)	(0.128)
Medicaid Income Limit * 10^{-3}	0.033	-0.130				
for Youngest Child (Maximum)	(0.076)	(0.095)				
Fraction of Children Eligible if			0.138	-0.167		
Mom Works 40 hrs/wk at Min.			(0.103)	(0.140)		
Fraction of Children Age-					0.146	-0.151
Eligible Under Expansions					(0.103)	(0.140)
Log Duration	0.499	0.538	0.501	0.539	0.501	0.539
	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)
(Log Duration) ^{2}	-0.190	-0.214	-0.192	-0.215	-0.192	-0.215
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Log Likelihood	-3038.8	-3019.6	-3038.0	-3019.8	-3037.8	-3019.9
Time Dummies	N	Y	N	Y	N	Y

Note: Standard errors in parentheses. All equations include a constant (not reported).

Table 4A: Estimated Coefficients from the Hazard Model
Transition from Welfare to Non-Welfare: Welfare Spells In Progress at Start

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.044	-0.035	-0.038	-0.033	-0.038	-0.033
	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
$Age^2 * 10^{-3}$	0.387	0.261	0.320	0.243	0.320	0.243
	(0.372)	(0.374)	(0.373)	(0.375)	(0.373)	(0.375)
Highest Grade Completed	0.064	0.064	0.063	0.063	0.063	0.063
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Non-White	-0.082	-0.089	-0.081	-0.083	-0.081	-0.083
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
Number of Children < 6	-0.052	-0.030	-0.055	-0.036	-0.055	-0.036
Years Old	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Age of Youngest Child	0.018	0.014	0.024	0.020	0.024	0.020
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Number of Children	-0.034	-0.003	-0.001	-0.007	-0.001	-0.007
	(0.032)	(0.033)	(0.032)	(0.032)	(0.032)	(0.032)
Divorced	0.165	0.159	0.163	0.161	0.163	0.161
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Separated	0.220	0.208	0.218	0.210	0.218	0.210
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Widowed	0.150	0.138	0.149	0.141	0.149	0.142
	(0.194)	(0.194)	(0.194)	(0.194)	(0.194)	(0.194)
Unemployment Rate	-0.061	-0.060	-0.066	-0.061	-0.066	-0.061
	(0.016)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)
AFDC Income Limit * 10^{-3}	-0.390	-0.330	-0.370	-0.390	-0.370	-0.390
(First Four Months)	(0.098)	(0.101)	(0.084)	(0.085)	(0.084)	(0.085)
Medicaid Income Limit * 10^{-3}	0.070	-0.070				
for Youngest Child (Maximum)	(0.051)	(0.064)				
Fraction of Children Eligible if			0.200	0.075		
Mom Works 40 hrs/wk at Min.			(0.075)	(0.098)		
Fraction of Children Age-					0.201	0.077
Eligible Under Expansions					(0.075)	(0.098)
Log Duration	-4.927	-4.991	-4.965	-5.001	-4.966	-5.002
	(0.915)	(0.918)	(0.915)	(0.918)	(0.915)	(0.918)
$(\text{Log Duration})^2$	11.557	11.624	11.660	11.664	11.663	11.666
	(1.753)	(1.762)	(1.755)	(1.763)	(1.755)	(1.763)
$(\text{Log Duration})^3 * 10^{-1}$	-84.759	-85.537	-85.678	-85.884	-85.702	-85.899
	(12.457)	(12.534)	(12.474)	(12.539)	(12.474)	(12.540)
$(\text{Log Duration})^4 * 10^{-2}$	252.900	256.700	256.200	257.800	256.200	257.900
	(37.744)	(38.046)	(37.807)	(38.065)	(37.807)	(38.066)
$(\text{Log Duration})^5 * 10^{-3}$	-268.000	-274.200	-272.100	-275.500	-272.200	-275.500
	(41.213)	(41.637)	(41.295)	(41.661)	(41.296)	(41.662)
Log Likelihood	-7207.8	-7186.5	-7205.1	-7186.7	-7205.0	-7186.7
Time Dummies	N	Y	N	Y	N	Y

Note: Standard errors in parentheses. All equations include a constant (not reported).

Table 4B: Estimated Coefficients from the Hazard Model
Transition from Welfare to Non-Welfare: Welfare Spells Beginning After Start of Sample

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Age	0.081	0.079	0.082	0.078	0.082	0.078
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Age ^{2} * 10^{-3}	-1.510	-1.490	-1.520	-1.480	-1.520	-1.490
	(0.486)	(0.489)	(0.486)	(0.489)	(0.486)	(0.489)
Highest Grade Completed	0.041	0.039	0.040	0.040	0.040	0.039
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Non-White	-0.066	-0.071	-0.068	-0.073	-0.068	-0.073
	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)
Number of Children < 6 Years Old	-0.035 (0.067)	-0.021 (0.068)	-0.034 (0.067)	-0.013 (0.068)	-0.034 (0.067)	-0.014 (0.068)
Age of Youngest Child	0.025	0.019	0.027	0.020	0.027	0.020
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Number of Children	0.036	0.069	0.038	0.028	0.039	0.029
	(0.041)	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)
Divorced	0.113	0.125	0.113	0.119	0.113	0.119
	(0.091)	(0.091)	(0.090)	(0.091)	(0.090)	(0.091)
Separated	0.219	0.235	0.219	0.226	0.220	0.226
	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)
Widowed	0.252	0.286	0.258	0.283	0.258	0.283
	(0.214)	(0.215)	(0.214)	(0.215)	(0.214)	(0.215)
Unemployment Rate	-0.008	-0.003	-0.008	-0.005	-0.008	-0.005
	(0.022)	(0.025)	(0.022)	(0.025)	(0.022)	(0.025)
AFDC Income Limit * 10^{-3} (First Four Months)	-0.380 (0.134)	-0.310 (0.136)	-0.420 (0.112)	-0.440 (0.113)	-0.420 (0.112)	-0.450 (0.113)
Medicaid Income Limit * 10^{-3} for Youngest Child (Maximum)	-0.020 (0.069)	-0.170 (0.088)				
Fraction of Children Eligible if Mom works 40 hrs/wk at Min.			0.036 (0.092)	-0.174 (0.125)		
Fraction of Children Age-Eligible Under Expansions					0.042 (0.092)	-0.162 (0.125)
Log Duration	-5.326	-5.294	-5.324	-5.292	-5.324	-5.292
	(1.100)	(1.099)	(1.100)	(1.099)	(1.100)	(1.099)
(Log Duration)^{2}	12.322	12.259	12.315	12.250	12.314	12.250
	(2.424)	(2.422)	(2.424)	(2.422)	(2.424)	(2.422)
(Log Duration)^{3} * 10^{-1}	-94.150	-93.700	-94.094	-93.622	-94.085	-93.622
	(19.351)	(19.328)	(19.350)	(19.324)	(19.351)	(19.323)
(Log Duration)^{4} * 10^{-2}	295.700	294.500	295.500	294.200	295.500	294.200
	(65.335)	(65.234)	(65.332)	(65.216)	(65.333)	(65.213)
(Log Duration)^{5} * 10^{-3}	-333.400	-332.300	-333.200	-332.000	-333.200	-332.000
	(79.065)	(78.918)	(79.061)	(78.888)	(79.063)	(78.883)
Log Likelihood	-3649.8	-3636.0	-3649.7	-3637.0	-3649.7	-3637.2
Time Dummies	N	Y	N	Y	N	Y

Note: Standard errors in parentheses. All equations include a constant (not reported).

Table 5: Estimated Coefficients from the Hazard Model
Transition from Employment to Welfare: Employment Spells In Progress at Start

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Age	-0.207	-0.205	-0.209	-0.209	-0.209	-0.210
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Age ^{2} * 10^{-3}	2.370	2.340	2.390	2.390	2.400	2.400
	(0.729)	(0.731)	(0.730)	(0.732)	(0.730)	(0.732)
Highest Grade Completed	-0.117	-0.119	-0.117	-0.118	-0.116	-0.118
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Non-White	0.605	0.601	0.607	0.597	0.607	0.597
	(0.111)	(0.112)	(0.111)	(0.112)	(0.111)	(0.112)
Number of Children < 6	-0.061	-0.044	-0.068	-0.026	-0.068	-0.025
years old	(0.108)	(0.108)	(0.107)	(0.109)	(0.107)	(0.109)
Age of Youngest Child	-0.063	-0.067	-0.066	-0.074	-0.066	-0.074
	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)
Number of Children	0.349	0.376	0.355	0.341	0.354	0.339
	(0.063)	(0.066)	(0.065)	(0.065)	(0.065)	(0.065)
Divorced	-0.239	-0.241	-0.241	-0.235	-0.241	-0.234
	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)
Separated	-0.113	-0.109	-0.114	-0.104	-0.114	-0.104
	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)
Widowed	-0.097	-0.093	-0.100	-0.080	-0.100	-0.079
	(0.301)	(0.302)	(0.302)	(0.302)	(0.302)	(0.302)
Unemployment Rate	0.102	0.088	0.104	0.088	0.105	0.088
	(0.033)	(0.037)	(0.033)	(0.037)	(0.033)	(0.037)
AFDC Income Limit * 10^{-3}	-0.070	-0.006	-0.003	-0.050	0.001	-0.050
(First Four Months)	(0.209)	(0.215)	(0.166)	(0.171)	(0.165)	(0.171)
Medicaid Income Limit * 10^{-3}	0.059	-0.080				
for Youngest Child (Maximum)	(0.113)	(0.140)				
Fraction of Children Eligible if			-0.002	-0.248		
Mom Works 40 hrs/wk at Min.			(0.148)	(0.190)		
Fraction of Children Age-					-0.013	-0.264
Eligible Under Expansions					(0.149)	(0.190)
Log Duration	-0.379	-0.401	-0.375	-0.399	-0.375	-0.399
	(0.051)	(0.054)	(0.051)	(0.054)	(0.051)	(0.054)
Log Likelihood	-2434.7	-2425.1	-2434.9	-2424.4	-2434.9	-2424.3
Time Dummies	N	Y	N	Y	N	Y

Note: Standard errors in parentheses. All equations include a constant (not reported).

Table 6: Estimated Coefficients from the Hazard Model
Transition from Employment to Non-Employment: Employment Spells In Progress at Start

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.122	-0.120	-0.121	-0.120	-0.121	-0.120
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Age ^{2} * 10^{-3}	1.350	1.320	1.340	1.320	1.340	1.320
	(0.267)	(0.267)	(0.267)	(0.268)	(0.267)	(0.268)
Highest Grade Completed	-0.073	-0.075	-0.074	-0.075	-0.073	-0.075
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Non-White	0.253	0.250	0.252	0.248	0.252	0.248
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Number of Children < 6 years	0.012	0.023	0.012	0.023	0.013	0.023
old	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Age of Youngest Child	-0.018	-0.020	-0.015	-0.017	-0.015	-0.017
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Number of Children	0.084	0.098	0.086	0.083	0.085	0.082
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Divorced	-0.165	-0.166	-0.164	-0.163	-0.164	-0.163
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Separated	-0.036	-0.033	-0.037	-0.032	-0.037	-0.032
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Widowed	0.085	0.086	0.085	0.085	0.085	0.085
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Unemployment Rate	0.019	0.025	0.016	0.024	0.017	0.024
	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)
AFDC Income Limit * 10^{-3}	0.000	0.033	-0.070	-0.090	-0.070	-0.090
(First Four Months)	(0.084)	(0.087)	(0.065)	(0.067)	(0.065)	(0.067)
Medicaid Income Limit * 10^{-3}	-0.050	-0.120				
for Youngest Child (Maximum)	(0.048)	(0.057)				
Fraction of Children Eligible if			0.034	-0.025		
Mom Works 40 hrs/wk at Min.			(0.055)	(0.068)		
Fraction of Children Age-					0.028	-0.031
Eligible Under Expansions					(0.055)	(0.068)
Log Duration	-4.680	-4.723	-4.690	-4.725	-4.689	-4.724
	(0.628)	(0.629)	(0.628)	(0.629)	(0.628)	(0.629)
(Log Duration) ^{2}	11.316	11.352	11.344	11.365	11.341	11.362
	(1.250)	(1.255)	(1.251)	(1.255)	(1.251)	(1.255)
(Log Duration) ^{3} * 10^{-1}	-86.189	-87.024	-86.453	-87.140	-86.425	-87.112
	(9.160)	(9.209)	(9.164)	(9.210)	(9.164)	(9.210)
(Log Duration) ^{4} * 10^{-2}	265.500	270.300	266.500	270.600	266.400	270.500
	(28.506)	(28.702)	(28.522)	(28.709)	(28.522)	(28.709)
(Log Duration) ^{5} * 10^{-3}	-289.700	-297.300	-291.000	-297.700	-290.800	-297.600
	(31.872)	(32.151)	(31.895)	(32.159)	(31.895)	(32.159)
Log Likelihood	-13375.4	-13347.6	-13375.7	-13350.0	-13375.8	-13349.9
Time Dummies	N	Y	N	Y	N	Y

Note: Standard errors in parentheses. All equations include a constant (not reported).

Table 7: Estimated Coefficients from the Hazard Model
Transition from Non-Employment to Employment: Non-Employment Spells In Progress at Start

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.034	-0.021	-0.032	-0.021	-0.032	-0.021
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Age ^{2} * 10^{-3}	0.071	-0.100	0.056	-0.110	0.055	-0.110
	(0.316)	(0.317)	(0.316)	(0.318)	(0.316)	(0.318)
Highest Grade Completed	0.122	0.120	0.122	0.120	0.122	0.120
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Non-White	-0.243	-0.240	-0.245	-0.239	-0.245	-0.239
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Number of Children < 6	-0.233	-0.208	-0.236	-0.210	-0.235	-0.210
Years Old	(0.047)	(0.048)	(0.047)	(0.048)	(0.047)	(0.048)
Age of Youngest Child	-0.010	-0.014	-0.008	-0.012	-0.008	-0.012
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
Number of Children	-0.005	0.022	0.026	0.023	0.026	0.023
	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)
Divorced	0.302	0.298	0.298	0.298	0.298	0.298
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
Separated	0.183	0.160	0.177	0.160	0.177	0.160
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
Widowed	-0.021	-0.020	-0.025	-0.018	-0.025	-0.018
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
Unemployment Rate	-0.053	-0.036	-0.055	-0.036	-0.055	-0.036
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
AFDC Income Limit * 10^{-3}	-0.510	-0.450	-0.430	-0.470	-0.430	-0.470
(First Four Months)	(0.094)	(0.096)	(0.078)	(0.079)	(0.078)	(0.079)
Medicaid Income Limit * 10^{-3}	0.114	-0.010				
for Youngest Child (Maximum)	(0.049)	(0.062)				
Fraction of Children Eligible if			0.152	0.034		
Mom Works 40 hrs/wk at Min.			(0.066)	(0.086)		
Fraction of Children Age-					0.157	0.042
Eligible Under Expansions					(0.066)	(0.086)
Log Duration	0.018	0.048	0.020	0.049	0.020	0.050
	(0.076)	(0.079)	(0.076)	(0.079)	(0.076)	(0.079)
(Log Duration) ^{2}	-0.121	-0.144	-0.122	-0.145	-0.122	-0.145
	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)	(0.024)
Log Likelihood	-9093.1	-9066.9	-9093.0	-9066.8	-9092.9	-9066.8
Time Dummies	N	Y	N	Y	N	Y

Note: Standard errors in parentheses. All equations include a constant (not reported).

Table 8: Estimated Coefficients from Logit Models:
Probability of Participating in AFDC

	On AFDC at start		Off AFDC at start	
	(1)	**(2)**	**(3)**	**(4)**
Age	-0.0235	-0.0222	-0.1637	-0.1679
	(0.0310)	(0.0315)	(0.0329)	(0.0330)
Age squared	0.0525	0.0545	0.2122	0.2149
	(0.0450)	(0.0458)	(0.0487)	(0.0490)
Highest grade completed	-0.0782	-0.0774	-0.1528	-0.1550
	(0.0162)	(0.0165)	(0.0120)	(0.0121)
Non-white	0.0653	0.0745	0.4819	0.4810
	(0.0728)	(0.0745)	(0.0820)	(0.0818)
# children < 6	0.0859	0.0309	0.0676	0.1208
	(0.0562)	(0.0582)	(0.0712)	(0.0727)
Age of youngest child	-0.0498	-0.0291	-0.0515	-0.0668
	(0.0116)	(0.0121)	(0.0120)	(0.0125)
# children	0.0019	0.0321	0.2740	0.2605
	(0.0400)	(0.0410)	(0.0493)	(0.0496)
Divorced	-0.2471	-0.2586	-0.3674	-0.3651
	(0.0871)	(0.0893)	(0.1061)	(0.1065)
Separated	-0.1741	-0.2054	-0.1053	-0.0972
	(0.0971)	(0.0999)	(0.1043)	(0.1045)
Widowed	-0.6150	-0.6431	-0.6165	-0.5867
	(0.2299)	(0.2375)	(0.2271)	(0.2263)
Unemployment rate	0.1185	0.0924	0.0285	0.0377
	(0.0203)	(0.0231)	(0.0211)	(0.0254)
AFDC income limit	0.0004	0.0005	0.0002	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Frac. elig. if mom	-0.5097	-0.0141	0.4221	0.0036
works 40 hrs at min.	(0.0831)	(0.1118)	(0.1005)	(0.1279)
Year effects	No	Yes	No	Yes
# obs.	79788	79788	221806	221806

Note: Standard errors in parentheses are corrected for repeated observations for individuals.

Table 9: Coefficients from Logit Models:
Probability of Being Employed

	On AFDC at start		Off AFDC at start	
	(1)	**(2)**	**(3)**	**(4)**
AFDC income limit	-0.0001	-0.0002	-0.00003	-0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Frac. elig. if mom	0.3102	-0.0454	-0.1029	0.0134
works 40 hrs at min.	(0.0900)	(0.1192)	(0.0502)	(0.0616)
Age	-0.0634	-0.0661	0.1920	0.1939
	(0.0367)	(0.0368)	(0.0184)	(0.0185)
Age squared	0.0920	0.0933	-0.2548	-0.2566
	(0.0544)	(0.0546)	(0.0259)	(0.0260)
Highest grade completed	0.1658	0.1659	0.1530	0.1536
	(0.0196)	(0.0197)	(0.0084)	(0.0084)
Non-white	-0.1083	-0.1162	-0.1415	-0.1399
	(0.0821)	(0.0826)	(0.0468)	(0.0469)
# children < 6	-0.3815	-0.3481	-0.1485	-0.1604
	(0.0667)	(0.0680)	(0.0451)	(0.0455)
Age of youngest child	0.0058	-0.0091	0.0275	0.0318
	(0.0129)	(0.0135)	(0.0065)	(0.0066)
# children	0.0104	-0.0080	-0.1621	-0.1559
	(0.0448)	(0.0452)	(0.0307)	(0.0307)
Divorced	0.4563	0.4646	0.3751	0.3746
	(0.0980)	(0.0991)	(0.0570)	(0.0571)
Separated	0.2430	0.2662	0.0606	0.0580
	(0.1120)	(0.1135)	(0.0610)	(0.0611)
Widowed	0.0884	0.1021	-0.6222	-0.6309
	(0.2861)	(0.2885)	(0.0943)	(0.0946)
Unemployment rate	-0.0908	-0.0801	-0.0475	-0.0490
	(0.0211)	(0.0249)	(0.0109)	(0.0127)
AFDC income limit	-0.0001	-0.0002	-0.00003	-0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Frac. elig. if mom	0.3102	-0.0454	-0.1029	0.0134
works 40 hrs at min.	(0.0900)	(0.1192)	(0.0502)	(0.0616)
Year effects	N	Y	N	Y
# obs.	79788	79788	221806	221806

Note: Standard errors in parentheses are corrected for repeated observations for individuals.